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Model Predictive Control (MPC) of System Identified Continuous Stirred Tank Reactor (CSTR) with Constraints

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***Abstract*— The continuous stirred tank reactor (CSTR) is a chemical system used in a wide variety of industrial applications that need the addition and removal of reactants and products continuously. This paper discusses the design of model predictive controller for unknown linear CSTR. The model of the CSTR is estimated by system identification method using random time series input and output data with constraint limits. The system identification method, estimated transfer model coefficients determined by using Gauss newton algorithm and validated. Then discrete model predictive control is utilized to discover the future state variables and output variables, and system adjusts the input flow rate(W1) to keep the output concentration (Cb) at the desired setpoint position. The objective function is developed and the optimization problem is addressed by using Quadratic programming (QP) with constraints. The simulation results with varying the parameters of MPC reveal the effectiveness of the proposed method.**

Keywords—continuous stirred tank reactor (CSTR), system identification method, model predictive control (MPC), Quadratic programming (QP).

I. INTRODUCTION

Model predictive control (MPC) was formulated in the 1970s and is mostly used in chemical industries. The model predictive control is a broad term used to refer to a range of control systems that uses a plant model to generate control inputs by minimizing an objective function. A model predictive control, essential components include prediction, optimization, and implementation of a receding horizon. MPC can predict future events and perform control actions to future outputs and targets. Many industries prefer PID controllers because of simple structure and tuning rules but PID controllers do not provide optimized output and constraints are not included. PID controllers for the multivariable process are not an easy task. For those cases, Model Predictive Controllers (MPC) proved to be optimal control ensuring that all control requirements are fulfilled. Researches on model predictive control had appeared in the early years, presenting it as a useful application in the chemical industry.

For almost 15 years, model predictive control has been a frequently employed control approach, presenting it as a useful application in the process industry. Qin, S. Joe, and T. Badgwell [1], have presented the dynamic plant model used for prediction analysis and linear optimization technique to obtain the control input, which is applied to the plant. In [2], equation error parameter estimation is utilized for the identification of a continuous-time model from sampling data. L Xie [3] has presented the issue of linear model mismatch with disturbances and the objective function solved using semidefinite programming, applied on continuous stirred tank reactor. Al-Qaisy [4] discussed Linear MPC on CSTR with the state-space model to compare the performance with Nonlinear MPC and PID controllers. In [5], presented the MPC with several local linear models compare with a single linear model and uses the convex optimization algorithm and compare with Nonlinear MPC applied on continuous stirred tank reactor. The analysis of most of the research work is discussed about the known model of CSTR is considered for developing an MPC.

Several nonlinear MPC (NMPC) also applied on CSTR system. In [6], a local linear state-space models using PID and nonlinear MPC is designed and compared the results. T. Wang [7], discussed the adaptive neural prediction model and nonlinear optimization used for the analysis of CSTR. G. Wang [8] has presented the NMPC uses with deep learning prediction model and gradient optimization algorithm on CSTR. Fuzzy based NMPC also developed in CSTR system [9]. The detailed stability analysis of MPC using linear matrix inequality is explained in [10]. The nonlinear models are complex and the nonlinear identification problem is more difficult. The solving of nonlinear optimization problems will require the fastest algorithms and also analyzing of stability and robustness further studies is required. The global minimum is not guaranteed and computation burden is still an open issue. In such cases, Linear MPC is required to formulate and solve the optimization problems is much easier and it has a definite convergency of local minimum.

This paper discussed Linear MPC of continuous stirred tank reactor with the model of the system is unknown. The CSTR system is identified by Gauss newton method using time series input-output data and the estimated transfer function used for control analysis purposes. The objective function is solved by using quadratic programming and the simulation analysis is done using MATLAB environment. The rest of the paper is organized as follows: Session II and Session III

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explains about CSTR system description and system identification respectively. The details of proposed control are depicted in Session IV. Then simulation and analysis are performed in Session V and conclusions are drawn in session VI.

II. System Description of CSTR

In this session, brief description of CSTR system is provided.

A. Continuous stirred tank reactor

The CSTR is a chemical reactor system mostly in process applications. The characteristics of CSTR are that uniformly mixed throughout the reactor, the composition of the output is the same as the composition of the reactor. Fig 1 shows the pictorial representation of CSTR. Here assumed that the mathematical model of the system is unknown and which is identified with the system identification method.

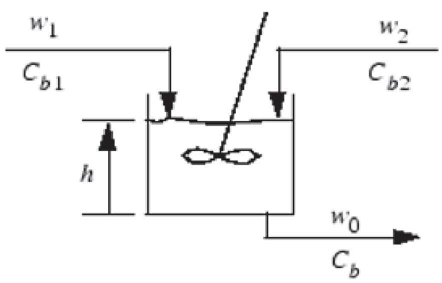

Fig. 1. Block diagram of CSTR

B. Specifications of continuous stirred tank reactor

The input output representation of CSTR is shown in Fig.2. The input flow rate $w_1(t)$ (Lmin^-1) of the concentration C_{b1}=24.9molL^-1 and the input liquid flow rate $w_2(t)$=0.1Lmin^-1 of concentration C_{b2}=0.1molL^-1. The height of the liquid level of CSTR is denoted by h(t) and which is not controlled in this paper. Let $k_1=k_2=1$ are the constants, termed as a rate of consumption. This paper aim is to maintain the output concentration product $C_b(t)$ molL^-1 by controlling the input flow rate $w_1(t)$ Lmin^-1. The random generated data set which contains the constrained input signal is given to plant in the range of $0\leq w_1(t) \leq 4$ Lmin^-1 and output varies in the range of between 20 and 23 molL^-1.

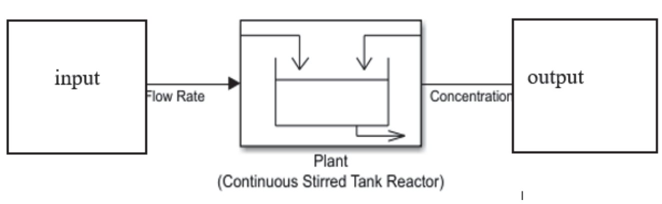

Fig. 2. Input-output model of CSTR

III. System Identification Method

System identification is a method for estimating the transfer models of a dynamic system from the input and output data of the plant. Gauss Newton based algorithm is implemented for the identification of CSTR.

A. Estimation of transfer function using System Identification Method by Using Gauss-Newton Algorithm

The Gauss-Newton algorithm is used to formulate the values of coefficients of the transfer function model which is the instrument variable (IV) approach. Consider a SISO continuous time-invariant system as

$$y_u(t) = G_0(p)u(t) \tag{1}$$

where p is written as $px(t)=\frac{dx}{dt}$. For system identification problem, continuous-time signals sampled at regular time interval $t=kT_s$ and the transfer function model written as

$$G(p,\theta) = \frac{B(P)}{A(P)} = \frac{b0+b1p+\cdots\ldots+bmp^m}{a0+a1p+\cdots\ldots+anp^n},\ a_n=1,\ n\geq m \tag{2}$$

$$\theta = [a_{n-1},\ \ldots\ldots a_0\ bm\ldots\ldots b_0]^T$$

One of the iterative algorithms called Gauss-Newton (GN) method can be used to solve nonlinear least-squares problems.

$$y_i = f(x_i, \theta) = G(p, \theta) \tag{3}$$

Let us suppose that we are given a set $(x_1, y_1),(x_2,y_2)\ldots(x_n,y_n)$ of n observations. At each of (x_i, y_i), while y_i is the measured value and $y = f(x_i, a0, a1, b0, b1)$ will be the estimated value. For simplicity $f(x_i, a0,a1,b0,b1)$ represented as $f(x_i)$. Let us linearize the nonlinear model at (j+1)th iteration level using Taylor series as

$$f(x_i)_{j+1} = f(x_i)+\frac{\partial f(xi)}{\partial a0}\Delta a0+\frac{\partial f(xi)}{\partial a1}\Delta a1+\frac{\partial f(xi)}{\partial b0}\Delta b1+\ldots \tag{4}$$

where the subscripts j,(j+1) denotes iteration levels, $\Delta a0=a_{0,j+1}-a_{0,j}$, $\Delta a1= a_{1,j+1}-a_{1,j}$, $\Delta b0 = b_{0,j+1}-b_{0,j}$, $\Delta b2= b_{1,j+1}-b_{1,j}$

The residual of errors is given by

$$e_i=y_i-f(x_i)= \frac{\partial f(xi)}{\partial a0}\Delta a0+\frac{\partial f(xi)}{\partial a1}\Delta a1+\frac{\partial f(xi)}{\partial b1}\Delta b1+\frac{\partial f(xi)}{\partial b2}\Delta b2.. \tag{5}$$

The matrix form is $\{D\}=[Wj]\{\Delta A\}$ (6)

The Jacobean of the model is given by

$$[W_j] = \begin{bmatrix} \frac{\partial f(x1)\,j}{\partial a0} & \frac{\partial f(x1)\,j}{\partial a1} & \frac{\partial f(x1)j}{\partial b0} & \frac{\partial f(x1)j}{\partial b1} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \frac{\partial f(xn)\,j}{\partial a0} & \frac{\partial f(xn)j}{\partial a1} & \frac{\partial f(xn)j}{\partial b0} & \frac{\partial f(xn)}{\partial b1} \end{bmatrix} \tag{7}$$

The matrix is $\{D\}_{n\times 1}$ is the error of each value and $\{\Delta A\}_{4\times 1}$ is the estimated parameters.

Apply the principle of least squares

$$[W_j]^T[W_j]\ \{\Delta A\} = [W_j]^T\{D\} \tag{8}$$

where, $a_{0,i+1}=a_{0,j}+\ \Delta a0$,$a_{1,j+1}=a_{1,j}+\ \Delta a1$,$b_{0,j+1}=b_{0,j}+\Delta b0$,$b_{1,j+1}=b_1,j+\Delta b1$

The procedure repeats till the solution converges

$$|\in ak| = \left[\frac{ak,j+1-ak,j}{ak,j+1}\right] < |\in ktolerance| \text{ and } \epsilon = 0.01 \tag{9}$$

IV. DISCRETE MODEL PREDICTIVE CONTROL

Using the estimated continues domain transfer function model, the model predictive controller is developed by transforming it to a discrete-time state-space model.

The form's state space model is written as

$$X(k+1) = A_r x(k) + B_r u(k) \tag{10}$$

$$y(k) = C_r x(k) + D_r u(k) \tag{11}$$

The change of state variable and input is written as

$$\Delta x(k+1)=A_r\Delta x(k)+B_r\Delta u(k) \tag{12}$$

$$y(k+1)-y(k) = C_r A_r \Delta x(k)+C_r B_r \Delta u(k) \tag{13}$$

By using the eq. (12) & (13)

The augmented model is given by

$$\begin{bmatrix}\Delta x(k+1)\\ y(k+1)\end{bmatrix} = \begin{bmatrix}A_r & {O_r}^T\\ C_r A_r & 1\end{bmatrix}\begin{bmatrix}\Delta x(k)\\ y(k)\end{bmatrix} + \begin{bmatrix}B_r\\ C_r B_r\end{bmatrix}\Delta u(k) \tag{14}$$

$$y(k) = [\,O_r\ 1\,]\begin{bmatrix}\Delta x_r(k)\\ y(k)\end{bmatrix} \tag{15}$$

where $O_r = [0\ 0\ \ldots.0]^T$. The augmented matrix in (15) is used to design the control.

A. State and Output variable for Predictive Analysis

The future state variable information up to single ahead and prediction horizon (Np) respectively is written by

$$x(k+1/k) = Ax(k) + B\Delta u(k)$$

$$x(k+Np/k) = A^{Np}x(k) + \ldots\ldots + A^{Np-Nc}B\Delta u(k+Nc-1) \tag{16}$$

where Nc control horizon, the future output equation is denoted by

$$y(k+1/k) = CAx(k) + CB\Delta u(k)$$

$$y(k+Np/k) = CA^{Np}x(k) + \ldots\ldots + CA^{Np-Nc}B\Delta u(k+Nc-1) \tag{17}$$

Because of the present and past information of the variables, define output and change in control in vector form

$$Y=[\,y(k+1/k)\ \ldots\ldots\ldots..\ .\ .\ y(k+Np/k)\,]^T$$

$$\Delta U = [\Delta u(k)\ \ldots\ldots\ldots\ldots..\ .\ .\ \Delta u(k+Nc-1)\,]^T$$

The (17) can be written in matrix form is given by

$$Y = G\,x(k) + \beta\,\Delta U \tag{18}$$

$$G=\begin{bmatrix}CA\\ CA^2\\ CA^3\\ .\\ .\\ .\\ CA^{Np}\end{bmatrix}$$

$$\beta = \begin{bmatrix}CB & 0 & . & . & 0\\ CAB & CB & . & . & 0\\ . & . & . & . & 0\\ . & . & . & . & .\\ . & . & . & . & .\\ CA^{Np-1}B & CA^{Np-2}B & . & . & CA^{Np-Nc}B\end{bmatrix}$$

B. Optimization without constraints

The primary goal is to determine the "optimal" control input vector ΔU that reduces the cost function. Assume the set-point information is included in a data vector.

$$R^T s = [1\ 1\ \ldots 1]\ r(k)$$

The cost function J is selected such that to reduces the error between actual value and reference value along with minimization of change in control input, and is given by

$$J=(Rs-Y)^T(Rs-Y)+\Delta U^T\bar{R}\Delta U \tag{19}$$

Equation (19) can be modified using (18)

$$J=(Rs-Gx(k))^T(Rs-Gx(k))-2\Delta U^T\beta^T(Rs-Gx(k)) + \Delta U^T(\beta^T\beta+\bar{R})\Delta U \tag{20}$$

The criteria for determining the minimal value is

$$\frac{\partial J}{\partial \Delta U}=0 \tag{21}$$

The control input is obtained by

$$\Delta U = (\beta^T\beta + \bar{R})^{-1}\beta^T\,(\overline{Rs}r(k) - Gx(k)) \tag{22}$$

The term $(\beta^T\beta+\bar{R})^{-1}$ is Hessian matrix. The first control input from ΔU at k instant, is applied using receding strategy while neglecting the remaining samples of sequence.

C. Problem formulation of DMPC with constraints

The constraints on control input, which is expressed as set of linear inequalities

$$\Delta u^{min} \leq \Delta u(k+1/k) \leq \Delta u^{max}$$

Two inequalities will be written as $-\Delta U \leq -\Delta U^{min}$

$$\Delta U \leq \Delta U^{max}$$

$$\begin{bmatrix}-I\\ I\end{bmatrix}\Delta U \leq \begin{bmatrix}-\Delta U^{min}\\ \Delta U^{max}\end{bmatrix} \tag{23}$$

The current control input can be represented as

$$u(k) = u(k-1) + \Delta u(k) = u(k-1) + [1\ 0\ 0\ 0]\Delta U$$

In general, the control input matrix considering the future interval with constraints can be expressed as:

$$\begin{bmatrix}u(k)\\ u(k+1)\\ .\\ .\\ .\\ u(k+Nc-1)\end{bmatrix} = \begin{bmatrix}I\\ I\\ .\\ .\\ .\\ I\end{bmatrix}u(k-1) + \begin{bmatrix}I & 0 & . & 0\\ I & I & . & 0\\ . & . & . & .\\ . & . & . & .\\ . & . & . & .\\ I & I & I & I\end{bmatrix}\begin{bmatrix}\Delta u(k)\\ \Delta u(k+1)\\ .\\ .\\ .\\ \Delta u(k+Nc-1)\end{bmatrix} \tag{24}$$

The constraints on control input sequence are applied as C1 and C2 correspond to the corresponding matrices is given

$$-(C1u(k-1) + C2\Delta U) \leq -U^{min}$$

$$(C1u(k-1) + C2\Delta U) \leq U^{max}$$

The objective function written in terms of constraints is given by

$$J=(Rs-Gx(k))^T(Rs-Gx(k))-2\Delta U^T \beta^T (Rs-Gx(k))$$
$$+\Delta U^T (\beta^T\beta+\bar{R})\Delta U \quad (25)$$

Subjected to inequality constraints

$$\begin{bmatrix} M1 \\ M2 \end{bmatrix} \Delta U \leq \begin{bmatrix} N1 \\ N2 \end{bmatrix} \quad (26)$$

$M1= \begin{bmatrix} -C2 \\ C2 \end{bmatrix}$,$N1= \begin{bmatrix} -U^{min} + C1u(k-1) \\ -U^{max} - C1u(k-1) \end{bmatrix}$, $M2= \begin{bmatrix} -I \\ I \end{bmatrix}$, $N2=\begin{bmatrix} -\Delta U^{min} \\ -\Delta U^{max} \end{bmatrix}$

D. Optimization problem for contrained DMPC

The objective function in (25) is reformulated as

$$J= \frac{1}{2} \Delta U^T E \Delta U + \Delta U^T f \quad (27)$$
$$M\Delta U \leq \gamma$$
$$E=(\beta^T\beta+\bar{R}) , \quad f= \beta^T(G-Rs)$$

Each phase of the active set technique solves an equality constraint problem, where the Lagrangian multiplier $\lambda i \geq 0$ and if $\lambda i \leq 0$ is defined as a relaxing constraint (i.e neglecting in the constraint problem. These active set methods are a subset of the Prime-Dual method and we have written decision variables as dual variables. This method is used to find the active and inactive constraints systematically. These types of problems were solved with Hildreth's programming.

E. Hildreth's Quadratic Programming

The general form of cost function in Hildreth's programming is expressed as

$$J= \frac{1}{2} x^T E x + x^T f \quad (28)$$
$$Mx \leq \gamma$$

For the convenience to solve the above problem, Let the decision variable $x=\Delta U$.

KKT equations of the optimization are the necessary conditions and are given by

$$Ex + f + M^T \lambda = 0 \quad (29)$$
$$Mx - \gamma \leq 0$$
$$\lambda^T (Mx - \gamma) = 0$$
$$\lambda \geq 0$$

The λ value is zero for inactive constraints and for active constraints the Lagrange multiplier $\lambda \geq 0$. For constraint identification, the dual approaches can be utilized, that is not active (thus eliminated from the solution). These dual types of problems are solved by using Hildreth's programming and λ is the assumed decision variable. The dual problem can be formulated by substituting KKT conditions (29) in primal objective function (28) and is given by

$$min_{\lambda i \geq 0} \left(\frac{1}{2} \lambda^T H \lambda+\lambda^T K + \frac{1}{2} f^T E^{-1} f\right) \quad (30)$$

where $K = \gamma+ME^{-1}f$, $H = ME^{-1}M^T$

The above conditions formulated and perform the line search procedure for finding solutions λ^*. The value λ^* contains inactive constrains the values zero and the positive terms regarding the active constraints. The positive term from the vector λ^*act is given by

$$\lambda^*_{act} = -(MactE^{-1}M^Tact)^{-1}(\gamma_{act} +MactE^{-1}f) \quad (31)$$

The Mact and γ_{act} are corresponding to data matrix with constraints and the final optimal solution is given by

$$\Delta U = x = -E^{-1}(f + M^T \lambda^*) \quad (32)$$

V. Simulation Analysis

In this session the simulation analysis of proposed system identification and controller is implemented. The result of system identification is performed by varying the order of the system. Then simulation analysis of DMPC for designed CSTR model is done with different Np and Nc. The transient performance of proposed controller is compared with PID controller using MATLAB environment.

A. System identification method

A proper input-output data is required for efficient system identification. Total of 300 pseudo random binary sequence (PRBS) in the range of $0 \leq w_1 \leq 4$ has been selected as input data flow rate (w_1)Lmin^-1. The output data, product concentration (Cb) molL^-1 in the range of $20 \leq Cb \leq 23$ molL^-1 will be generated from CSTR using matlab environment. The collected input-output data is shown in Fig. 3.

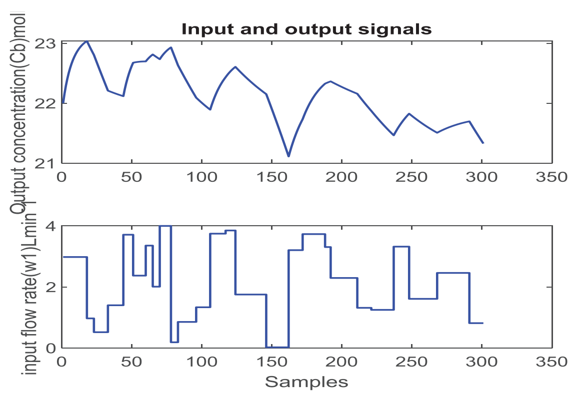

Fig. 3. Time-series input of flow rate (w_1)Lmin^-1and output data Of concentration(Cb)

The system identification using Gauss-Newton algorithm is performed by varying the system order. Table I shown the performance after the identification of CSTR by varying the system order. It is show that the second-order transfer function model gives a better fit to estimation data percentage and less prediction error, compared to all remaining transfer function models. Fig. 4 shows the actual output value and estimated CSTR output value for second order system. Best fitting can be observed between the actual value and obtained value with mean square error (MSE) as 0.00393. The estimated transfer coefficients corresponding to second order CSTR is given by a0=0.0001738, a1=0.09517, b0=0.001604, b1=0.0373.

The estimated second-order transfer function is written as

$$G(s)=\frac{0.0373S+0.001604}{S^2+0.09517S+0.0001738}$$

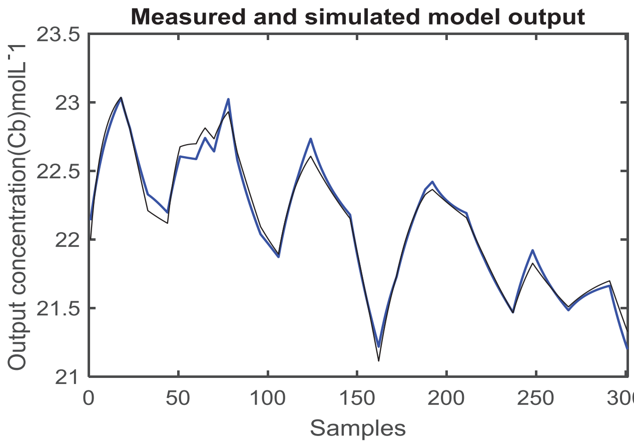

Fig. 4. validation of 2^{nd} order model after estimation, Fit to estimation data=88.1%

TABLE I. COMPARISON OF DIFFERENT TRANSFER FUNCTION MODELS

Poles (P) and Zeros (Z)	Order	Fit to Estimation data (%)	Final prediction error (FPE)
P=1,Z=0	1^{st} order	67.76%	0.02216
P=2,z=1	**2^{nd} order**	**88.1%**	**0.00393**
P=3,z=1	3^{rd} order	56.78%	0.04118
P=4,z=1	4^{th} order	13.11%	0.1686

This 2^{nd} order model is utilized in the design and implementation of discrete model predictive control (DMPC) of CSTR. The discrete-time state-space model matrices with sampling time chosen Ts=0.1 is given by

$$Ap=\begin{bmatrix}0.9905 & (-1.7298*10^{-5})\\ 0.0995 & 1.000\end{bmatrix},$$

$$Bp=\begin{bmatrix}0.0995\\ 0.0050\end{bmatrix},\ Cp=[0.0374\ 0.0016]\ ,\ Dp=[0]$$

B. Comparision of DMPC with PID controller of CSTR

After the system identification, DMPC is designed. Initially an unconstrained DMPC was designed for comparison with PID controller. A step reference of 23 $molL^{-1}$ is selected for comparative study. The following parameters are chosen for DMPC, Np=8, Nc=4 and $\bar{R}$=0.1. The Ziegler-Nichols reaction curve tuning method is employed for developing the PID controller. The parameters of PID controller is found as Kp=2.207, τ_i=100 and τ_D=25. The response of PID and DMPC for the above condition is shown in Fig. 5. It can be shown that DMPC gives less overshoot and less settling time than the PID controller. The controller effort for the both controllers are also shown in Fig. 5. Less magnitude of control effort is exhibited in DMPC than PID controller. This indicates the effectiveness of proposed DMPC controller on CSTR system. It is noted that, in both controllers, controller input is violating the constraints in the range of 0≤u≤4 since there is a sudden change at starting time and after some time it's able to maintain control input constant value.

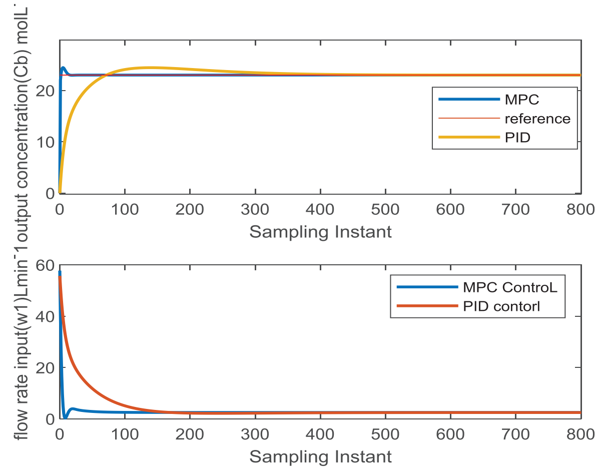

Fig. 5. comparison DMPC with PID with a set point at 23 molL^-1 and sampling time Ts=1

C. Discrete MPC without constraints for CSTR

In this subsection, the performance of DMPC is studied for the variable step reference input change from 20 to 21, 22, 23 molL^-1. The output response of DMPC based CSTR system with Np=20, Nc=4 and $\bar{R}$=0.5 is shown in Fig. 6.

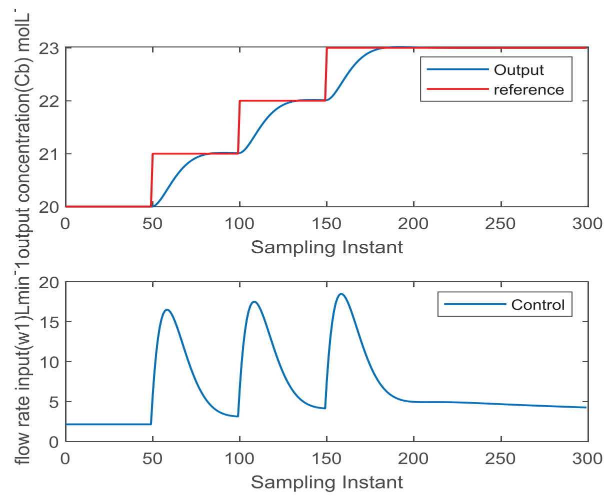

Fig. 6. variable step reference input change of output centration response (Cb) molL^-1 and input flow rate(w1)Lmin^-1 , with Np=20, Nc=4, Ts=0.1 sec

From Fig.6 it is identified that the output response reached the different setpoints with an overshoot of 0.0952%, simulation time of 0.0313 sec, and the tracking root means square error (RMSE) of 1.6605. It can be also observed from Fig. 6 that, the controller input is violating the constraints, but drastic variation in control input is lesser compared to the case V.B.

D. Discrete MPC with constraints for CSTR

In this subsection, the performance of DMPC with constraints is studied for variable step reference input change from 20 to 21, 22 and 23 molL^-1. The output response of DMPC based CSTR system with Np=10, Nc=4 and $\bar{R}$=0.1 is shown in Fig. 7. It can be seen that proposed system reaches the target values with an overshoot of 0.14%. It is clearly noted that the control inputs are satisfying the constraints criteria, hence the control effort for this proposed controller is considerably reduced. The settling time of DMPC with constraints is more compared with DMPC without constraints.

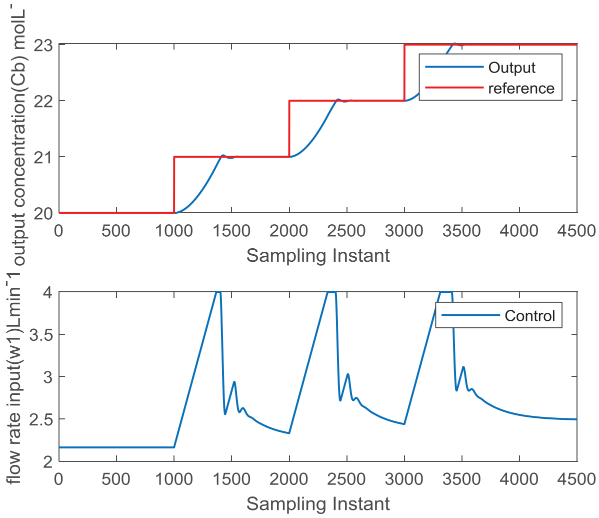

Fig. 7. Simulation result of output concentration (Cb)molL^-1 and input flow rate(w1) with Np=10, Nc=4

The simulation has been performed by varying the control horizon. Fig. 8 shows the performance of CSTR for variable step reference input change with a set point from 20 to 21,22,23molL^-1, and Np=20, Nc=4. It is shown that by increasing the prediction horizon, the overshoot considerably reduces (to zero). The chattering on the control input is substantially reduced in this case compared to DMPC with lower values of Np.

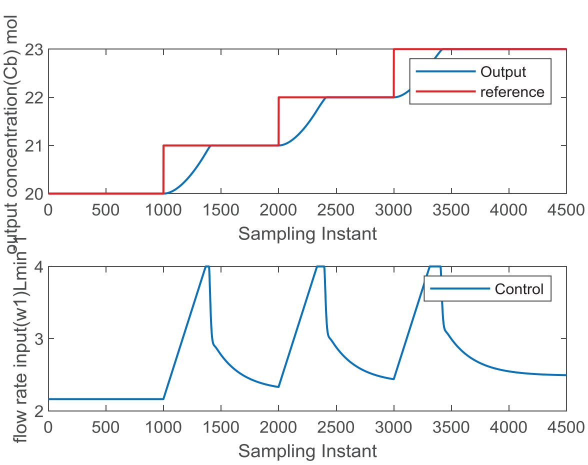

Fig. 8. simulation result of output concentration (Cb)molL^-1 and input flow rate(w1) with Np=20, Nc=4

The performance of the system is evaluated by changing the control horizon also. Fig. 9 shows the system performances with DMPC along with constraints for the case Np=20 and Nc=8. The considerable performance variations are not seen for the case of increasing the value of prediction horizon.

A comparative performance study of DMPC with constraints under various conditions are shown in Table II. It is noted that, if increasing the prediction horizon from Np=10 to 20, reducing the overshoot around the settling point and prediction accuracy was increased. For the case, if increasing control horizon (Nc), it increases computational cost but it hasn't improved the performance much. The tracking error is almost same for tracking the output concentration (Cb) molL^-1 in all the cases of different control horizons. The mean absolute value of performance index (J) is also shown in Table II with respect to various Np and Nc. The performance cost increases when the number of prediction horizon increases, whereas it decreases when control horizon increases. The mean absolute value of performance index for DMPC without constraints is comparatively very less, which is in the range of 0.043. Hence incorporating constraints on DMPC provides substantial increment in performance cost.

Hence the proposed DMPC control strategy shows that output concentration (Cb) can track the response with different setpoints and control input signal is within constraints limits.

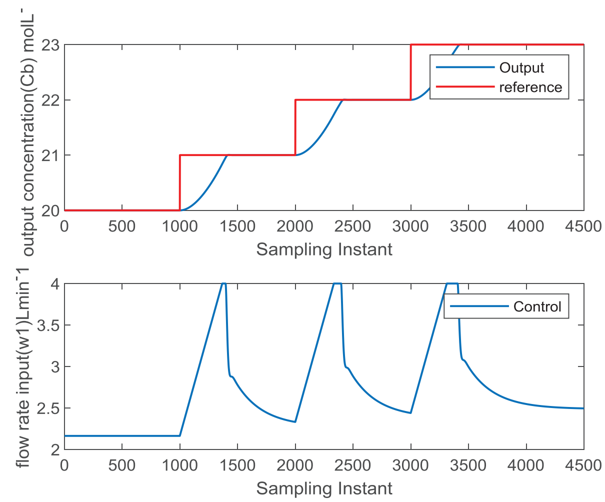

Fig. 9. simulation result of output concentration (Cb)molL^-1 and input flow rate(w1) with Np=20, Nc=8

TABLE II. COMPARATIVE ANALYSIS OF VARIABLE STEP REFERENCE CHANGE OUTPUT (CB) AND INPUT (W1)

	Np=10			Np=20		
	Nc=2	Nc=4	Nc=8	Nc=4	Nc=8	Nc=18
Tracking error	1.6393	1.6214	1.6215	1.6013	1.5911	1.590
Overshoot	0.14%	0.14%	0%	0%	0%	0%
Mean absolute value of J	1.218	1.189	1.179	1.549	1.442	1.428
Simulation time	0.142sec	0.5sec	0.578sec	0.515sec	0.52sec	0.562 sec

VI. CONCLUSIONS

In this paper, a discrete model predictive controller was designed for unknown continuous stirred tank reactor (CSTR). Estimated the transfer function using system identification through input-output time series data and the transfer function converted to discrete state-space model for analysis of DMPC. The objective function formulated and the optimization problems solved by using Quadratic programming with and without constraints. The analysis of active and inactive constraints is done using Hildreth's quadratic programming. The simulation results show that the output concentration (Cb) molL^-1 is maintained the desired set point position and reducing the error for the proposed DMPC controller compared to PID controller. If prediction horizon increases, the output response was reducing the overshoot around the settling point and prediction accuracy was increased. The simulation time increases with an increase with Nc. The tracking error is almost the same for all the values of Nc. Further analysis can be done for better accuracy and less settling time and computation burden, by developing better optimization algorithm and prediction model.

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